Control and System Identification via Swarm and Evolutionary Algorithms

Tayebeh Mostajabi, Javad Poshtan

Abstract— A central topic of swarm intelligence is the investigation of different types of emergent collective behaviors in swarms. This article focus on the swarm intelligence applications in control and system identification. Particle swarm optimization (PSO), a novel population based stochastic optimizer with fast convergence speed and simple implementation and genetic algorithm, have been successfully applied to solve system identification optimization problems. In addition, PSO and ant colony optimization (ACO) have been applied as a navigation algorithm in swarm robots. Some of the recently proposed swarm based metaheuristics such as bacterial foraging optimization algorithm (BFOA), wasp optimization algorithm (WOA), bee optimization algorithm (BOA) and Physarum Solver will need further investigation to assess their potential for generating state-of-the-art algorithms that are useful for this area.

Index Terms— adaptive control; evolutionary algorithm; global minimum, local minima, robotics; swarm intelligence; system identification.

1 Introduction

SWARM and evolutionary algorithms are useful tools that have been inspired by the natural behavior between organisms and their real world interactions or even the laws of physics and the relationship between particles and objects. Maybe the birth of such algorithms began with genetic algorithm. GA was presented by John Holland in the 60's AD with the taking idea of behavior of chromosomes in cell division in living organisms. This is an optimization algorithm that in addition to solving optimization problems, is applied in various applications from music to complex engineering problems [1]. About 1990, another famous algorithm named ant colony optimization (ACO) is introduced by Dorigo Moroco [2] which is inspired from ant behavior where finding the shortest path from the nest to the food source. In 1995 particle swarm optimization (PSO) was born according to behavior of flocks of migratory birds [3]. Since then, many researchers have studied on such algorithms. Some of them found and introduced another novel algorithms. These new algorithms can be divided into three categories: The first was created considering the behavior of other living organisms, for instance, bacterial foraging optimization algorithm (BFOA) mimics how bacteria forage over a landscape of nutrients optimally[4], or bee colony algorithm is inspired honey bees when they return to the hive and tell the others about finding a good foraging site via the famous dance language, or principles from self-organized task allocation and social hierarchy within a colony of wasps is modeled as wasp algorithm for scheduling. or also physarum solver, physarum is a slime mode that is built by a kind of diatom named plasmodium in order to reach to the food optimally [5]. The second category like SOA (seeker optimization algorithm) is simulated some social human behavior [6]. or Imperialist Competitive Algorithm that is based on dominance of stronger countries on weaker states [7] and the third one has been developed according to fundamental physics laws [8-10].

In fact, all of these algorithms are optimization techniques, some of them like ACO more successful in local and some other like PSO in global optimization problems. Their high ability in solving complex optimization problems Led another group of researchers seeking to apply them directly or as a combination with each other or other computational intelligence algorithms [11] or even conventional methods [12-14,23] to find simpler solutions for solving specialized challenging issues in their own fields. In this regard, it can be pointed to the increasingly influence of swarm and evolutionary computation in control engineering applications.

Nowadays, control engineering has been found many applications in various sections of human life. In control system engineering, the desired output is applied as input to system and the tendency is reaching the desired output and tracking input by output.

A system under the control can be a plain that should track the special path or a robot with special task or even a biological system such as brain, heart or any kind of disabled human body that we want to improve its faults with a suitable controller and even so the system under control can be some sections of social human life such as traffic jam, the fluctuate of burse and other social living difficulties.

Swarm and evolutionary algorithms have been find applications in many applied control engineering. for instance, in various controller designs, path tracking, robotic and swarm robots and also in system identification.

This article attempts to review some parts of influence of these algorithms in control engineering, controller designing, robotics and specially their applications in adaptive control and system identification.

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2 System Identification

In order to reach an acceptable control for system or plant, The primary step is, finding a suitable mathematical model. finding a suitable model is the basic work and also the most difficult one in control engineering. If we can obtain a proper model for under the control system, controller designing and good tracking is probable. Vice versa, If we do not have a proper model, we would hardly succeed to design a fine controller and tracking.

In cases where the control system, is a small device and relatively detailed map of all its components are available, an appropriate model can be obtained by using the laws and theories of electricity, magnetism, mechanics, and thermodynamics. But in many cases, such a detailed map is not available. but fortunately there is another approach that is system identification.

In system Identification configuration, in order to find an appropriate model, we need a set of informative data. This data set is produced by applying a proper input to the system and calculate the equivalent output. After that we should do curve fitting and find the best descriptor model for available data set.

Depending on what method to use and what kind of model we selected for identification, several well-known classical methods for estimating unknown parameters of the model have been introduced [15-16]. These methods are very successful in some situations but they do not succeed in many cases efficiently. Hence, in recent decades, researchers tend to utilize new methods including swarm intelligence and preparing them for system identification.

In many cases, the state-space model is used for modeling systems and processes. In these cases swarm intelligence algorithms can estimate the unknown parameters. For instance, in [17], ACO is used for parameters identification of induction motor. ACO is based on finding the shortest path. Ants deposit pheromone in their journey from nest to the feed. The other ants in the colony sense pheromone and prefer to select a path that its pheromone concentration is higher. Ants that have accidentally chosen the shorter path, would return sooner. Inchmeal, pheromone concentration of the shortest path is more and more naturally due to faster traffic so that after a while, colony are concentrated on the shortest path. In ant colony optimization algorithm, a number of artificial ants build solutions to an optimization problem and exchange information on their quality via a communication scheme that is reminiscent of the one adopted by real ants [2]. Therefore the problem should convert to an especial graph in which artificial ants try to find the shortest path. In [17] state space model is employed to estimate parameters of induction motor where all of the estimated parameters are divided in to 5 groups and their boundary conditions are adjusted according to our knowledge about induction motor. after that an especial graph path is defined for artificial ants and the quality of selected path by each ant is calculated according to selected nods in its journey in the graph.

Chaotic ant swarm in [18-19] is used for parameter identification in chaotic systems. In [20] Chaotic Particle Swarm Optimization that is more capable of PSO to find global minimum and escape from local minima, is employed for nonlinear identification according to control a nonlinear yo-yo motion system.

Adaptive filters are used to model many processes in system identification. It is generally shown in figure(1), The adaptive filter attempts to iteratively determine an optimal model for the unknown plant, based on some function of the error between the output of the adaptive filter and the output of the plant. The optimal model or solution is attained when this function of the error is minimized. The adequacy of the resulting model depends on the structure of the adaptive filter, the algorithm used to update the adaptive filter parameters, and the characteristics of the input signal [14]. But in many cases especially where infinite impulse response (IIR) or nonlinear adaptive filter such as a neural network or polynomial filter is applied, the fallowing error function is multimodal. Hence many classical methods such as Least Mean Square (LMS) or back-propagation are trapped to local minima and could not find the optimal model. On the other hand swarm intelligence (SI) optimization methods are very powerful optimization techniques for many multimodal landscapes.

As a result of this, several researchers have proposed various methods in order to use SI and evolutionary algorithms in adaptive filtering applications, for instance, in [13-14,21-28] genetic algorithm is utilized to estimate the parameters of an adaptive filter model in order to use in system identification where fitness function based on mean squared error (MSE) between the unknown plant and the estimated model is used. GA behave as an adaptive algorithm in the circled process. At first the algorithm begin with the random set of possible solutions that each one is embedded in one chromosome. Each chromosome has the number of genes that is equal with the number of unknown parameters of the adaptive filter. At every generation, the fitness of each individual (chromosome) is evaluated by a predetermined fitness function. An individual with lower fitness value is considered. The population is then evolved based on the circled process of natural selection, survival of the fittest, and mutation. This cycle is continued in order to find the optimal solution.

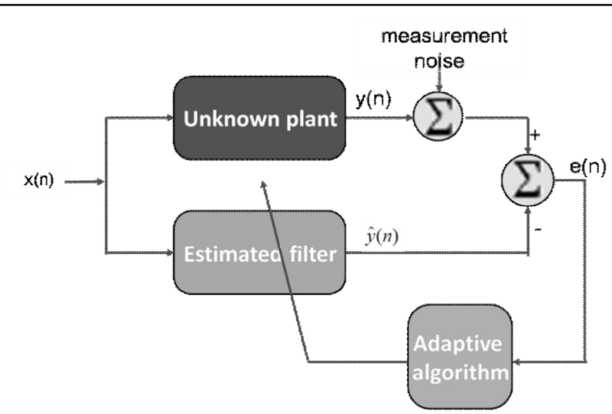

Fig. 1. Adaptive system identification configuration using output error.

Another popular technique in this category is Particle Swarm Optimization. PSO is the global optimization algorithm with fast convergence that is applied as an adaptive algorithm in system identification [13,14,30-34]. In PSO the population search the optimal solution in D dimensional space based on fitness function. D is the number of unknown parameters of the adaptive filter model. Each particle has its own position (X_i) and velocity (V_i) vectors by D dimension (see equations (1) and(2)) that are updated in each iteration respect to equations (3) and (4). The cycle of the algorithm is iteratively continued in order to find the optimal solution. Figure(2) illustrates the PSO circle for adaptive filtering in system identification.

$$x_i = (x_{i1}, x_{i2}, \ldots, x_{iD}) \quad (1)$$

$$v_i = (v_{i1}, v_{i2}, \ldots, v_{iD}) \quad (2)$$

$$x_{iD}(k+1) = x_{iD}(k) + v_{iD}(k+1) \quad (3)$$

$$v_{iD}(k+1) = \omega * v_{iD}(k) + c_1 * \mathrm{rand}_1() * (P_{iD} - x_{iD}) + c_2 * \mathrm{rand}_2() * (P_{gD} - x_{iD}) \quad (4)$$

In above equations, c_1 and c_2 are accelerator constants that are adjusted by user. *w* is the weight that controls the previous velocity vector. $P_i=(P_{i1},P_{i2},\ldots,P_{iD})$ is the personal best position (pbest) found by particle *i*, and $P_g=(P_{g1},P_{g2},\ldots,P_{gD})$ is the global best position (gbest) found in a whole swarm [5,13].
Since generally finding the optimal answer in produced multimodal error surface is challenging, researchers have tried to enhance PSO convergence for this issue. For instance, in [13], two main weaknesses of PSO, outlying particles and stagnation is modified and the modified algorithm is used for adaptive filter modeling. Other examples in this area are [35-37].
The other algorithm that is employed for adaptive filtering in system identification is ACO [38]. In [39] cat swarm optimization is used for infinite impulse response (IIR) modeling. Other examples are artificial bee colony algorithm [40,41] and BFOA [4,42] that are utilized as an adaptive algorithm for estimated parameters of a model based on adaptive filter.
Chaotic ant swarm that is a kind of modified ant algorithms is synthesized with type III fuzzy method in [43] and the combination is used as an adaptive algorithm. [44] first introduced a novel fitness function and then embedded it in PSO for robust system identification. Differential evolution that is an evolutionary algorithm like GA, is utilized in [45] as an adaptive algorithm.
Estimating unknown parameters of a model for multivariable systems is a challenging problem because of couplings and interactions between channels. In this situations, adaptive algorithm should be capable in local searching besides global one. In [46] a modified genetic algorithm, named memetic algorithm that has global and local searching capability, is applied as an adaptive algorithm for multivariable system identification.

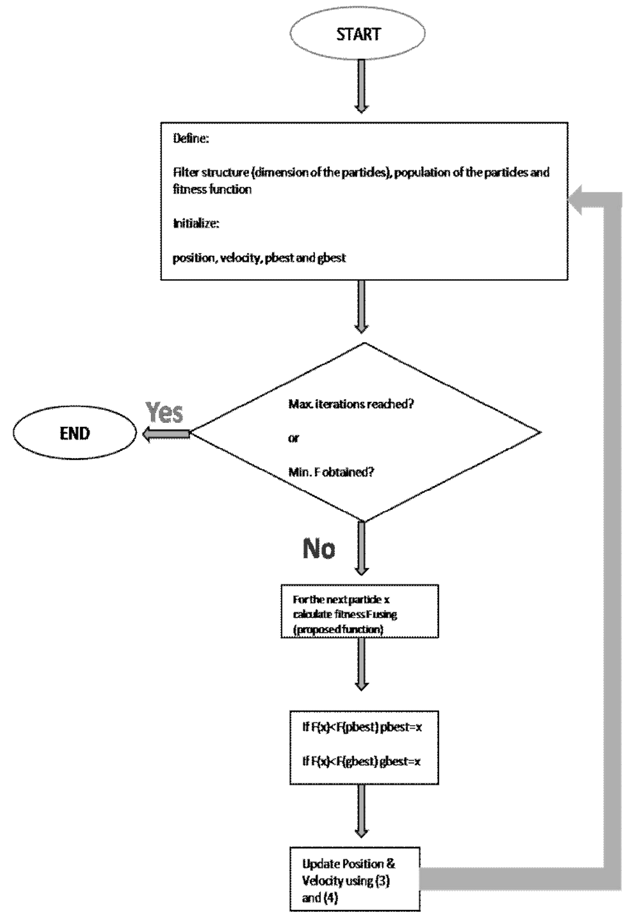

Fig. 2. Flowchart of PSO used for adaptive filtering in system identification.

3 Swarm Intelligence for Controller Designing and Adaptive Control

Swarm and evolutionary algorithms are applied in adaptive control for estimating unknown parameters of model or controller. model estimation with these algorithm where discussed in previous section has many applications in adaptive control based on identification, But these algorithms can also be applied for tuning parameters of controller. For instance, a PID controller can be shown $k_P + k_I/s + k_D s$ in general that k_I, k_I and k_D are adjusted according to conditions and desired target of the problem. In addition, the dynamic of the plant and the quality of feedback loop bound defined region of these parameters, so that if parameters has a value out of the region, system probably tend to instability.

In PID controller design, for self-tuning or fixed mode, swarm and evolutionary algorithms are useful tools. In fixed mode, the algorithm tries to find the best values for PID coefficients according to bounded region based on error signal. In self tuning or auto tuning mode, after adjusting the coefficients, system output is checked by the algorithm consistently or occasionally. Whenever system output is undesirable, that is probably happened because of changing circumstances or the dynamic plant, The PID coefficients are adjusted by the algorithm for this new situation again. For applying such algorithms in on-line applications, they should able to find the optimal solution with acceptable speed convergence. [47] is an example for this issue in which PSO is used to adjust self-tuning and fixed PID controller for a static synchronous compensator (STATCOM).

design of fuzzy controllers is a rather new method, in which controller built of fuzzy system. In fact, the control signal is determined by fuzzy rule base. The quality of fuzzy controller depends on how to define the corresponding fuzzy rule base. As a result of this, swarm intelligence can be applied to optimize the fuzzy rule base that is increase the quality of fuzzy controller [48-52].

4 Robotics and Swarm Robots

Swarm intelligence has been demonstrated to be a useful tool in target search applications such as collective robotic search (CRS) [11]. [53] is probably the first project in this issue that began in 1992 and its results are published in 1995. Where each robot in swarm robots weighs amount 10kg and has ability to lift and carry 150kg load. The associated navigation algorithm is inspired from real ants where they help each other to carry heavy pieces. At first, when the command signal is sent. The first robot that receives this signal will be a leader of swarm. If the leader becomes out of order, the other is replaced rapidly. Each robot has its own decentralized control. Nevertheless, all swarm robots are control globally by central computer system. Robots communicate with each other by adhoc system. In addition, the position of each one is informed to central computer system by GPS. Flexible PVC material is used to build their bodies. So that they crawl under heavy mass, then a bladder object, embedded in their body is inflated by compressor and the heavy mass is lifted.

Several robotics applications such as rescue and planetary or underwater exploration are performed in very unstructured and partially unknown environments. Robots operating in such environments should display a high degree of mobility, versatility, and robustness to very different and time-varying operating conditions[54]. As a result of this, the other project began in 2002 and still continues. (see www.aco-metaheuristics.org for more information). These swarm robots have decentralized robust control by their own PIC microprocessors. Their navigation algorithms are inspired from actual ants when make living bridges to cross large gaps or help each other to cross Steep slopes. These robots have a strong gripper to lift each other, If necessary. Most parts are flexible. They are light and have 660g weigh, Therefore can lift each other easily. They communicate with each other by a local network and also communicate with external computer. Whole swarm are controlled by platform control globally. Each robot can cross 45mm gape, 23mm step and 60 degree slope. However these ability is increase when they are twice. and grows increasingly when they are swarm.

In [55] PSO is used as a navigation algorithm for a group of mobile robots in which they can locate a specified target in a high risk environment with extreme efficiency.

In [56] a group of mobile robots is simulated where their movement are as the same as particles in PSO algorithm and in fact real flock of birds in sky. These swarm robots try to find odor source according to obstacles environment. In order to escape local minima, each robot have amount of electric charge. As a result, They repel each other in very closed distances. Therefore If one of them trapped to local minimum. The other do not converge it. and have chance to find the odor source.

4 Conclusion

This paper tried to review briefly some parts of influence of swarm and evolutionary algorithms in control engineering, controller designing, robotics and specially their applications in adaptive control and system identification. PSO with faster convergence speed and simpler implementation than genetic algorithm**,** has been successfully applied to solve system identification optimization problems and can be employed for on-line applications in self tuning controller design in adaptive control. In addition, swarm robots that have been inspired by the natural behavior between swarm in real word, can be useful for several applications such as rescue and planetary or underwater exploration. PSO and ACO have been applied as a navigation algorithm in robotics.

Nevertheless, swarm intelligence and evolutionary computation will need further investigation to assess their potential for generating state-of-the-art algorithms that are useful for this area.

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